Journal of Innovation and Development
ISSN: 2958-4752 | Vol. 11, No. 2, 2025

The Left-tail Momentum of The Chinese Stock Market

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Abstract: In the research on the correlation between "risk and return", the capital pricing model and arbitrage pricing model have always occupied an important position, but in recent years, when the research market continues to expand and the research indicators are constantly enriched, the negative correlation between tail risk and cross-sectional returns of stocks has received more and more attention. Studies have used data from the U.S. stock market to find that the relationship between the left-tail risk of individual stocks and their cross-sectional returns is significantly negatively correlated, that is, stocks with higher left-tail risk have lower future returns. This finding contradicts the positive correlation between return and risk under traditional financial research, and then promotes the formation of left-tail risk anomalies. However, compared with the US stock market, the overall development time of China's stock market is relatively short, there are many retail investors, and market participants often do not have professional investment knowledge, so information asymmetry prompts blindly following market participants to invest irrationally like a herd, and most of the anomalies in asset pricing can be explained from the perspective of behavioral finance. Therefore, this paper draws on his research ideas to examine whether there is left-tailed momentum in the Chinese stock market, and whether the company characteristic indicator can strengthen this relationship and explain it through behavioral finance. This paper studies the period from January 1, 2000 to December 31, 2022, and aims to explore the cross-sectional correlation between left-tail risk and stock return in the coming month, using the return of all stocks in the Shanghai and Shenzhen markets to measure left-tail risk at risk. Firstly, the fundamental relationship between risk and return is explored through univariate combination analysis, and then the role and marginal contribution of company characteristic indicators on the relationship between risk and return are considered from the perspective of behavioral finance, considering common company characteristic indicators, such as book-to-market capitalization ratio, and indicators linked to poor investor information, such as analyst coverage, etc., to consider the role of corporate characteristic indicators on the relationship between risk and return from the perspective of behavioral finance. The results show that there is a significant left-tail momentum in China's stock market, that is, there is a negative correlation between left-tail risk and expected return, and the phenomenon of left-tail risk is more obvious in stocks with retail holdings and low analyst attention. When the yield is adjusted by the four-factor model, the performance of the left-tail momentum effect will be significantly strengthened, which is significantly better than the traditional capital asset pricing model and the three-factor model. In the research sense, frequent "black swan" events have made investors pay more and more attention to the huge risk contagion chain behind small probability events or extreme events, and at the same time suggest that the tail risks of relevant government departments may pose a major threat to the systematic smooth and orderly operation of the entire financial market.

Keywords: Asset pricing; Left tail risk; Analyst focus.

1. Introduction

1.1. Research Background

Over recent decades, the interdependent relationship between asset risk and return, namely the asset pricing problem, has remained a pivotal focus in both theoretical and empirical financial research. In measuring financial asset risk, Markowitz's mean-variance model gained widespread adoption due to its simplicity and interpretability. Subsequently, the Capital Asset Pricing Model (CAPM) introduced systematic risk as the proxy for cross-sectional return differentials, positing a positive linear relationship between undiversifiable systematic risk and expected returns. This paradigm established the dominance of the risk-return positivity hypothesis in financial academia. However, as markets expanded and analytical dimensions diversified—marked by the proliferation of asset pricing factors proposed by foreign scholars and their applicability tests in domestic financial submarkets by local researchers—the traditional risk-return positive correlation has gradually eroded, with negative associations attracting growing empirical attention.

Emerging evidence reveals that financial asset returns frequently deviate from normality, exhibiting leptokurtosis and fat-tailed distributions. The "left tail" refers to the lower-probability segment of the return distribution, where extreme events exert disproportionate influence. This conceptualization has elevated "left-tail risk" as a critical research focus. J.P. Morgan first introduced Value-at-Risk (VaR) as a measure of left-tail risk, which, owing to its intuitive interpretation, has become a robust metric for analyzing tail risk-return dynamics. Contemporary research increasingly emphasizes dimensionality expansion through characteristic indicators. For instance, Bali (2003) employed VaR to quantify stock tail risk[1], marking the emergence of left-tail risk as a novel analytical frontier. This trajectory underscores the evolving methodological sophistication in disentangling the complex interplay between tail risk exposures and cross-sectional return anomalies.

1.2. Research Significance

The rise of behavioral finance has spurred domestic scholars to innovate in identifying pricing factors, particularly those rooted in behavioral anomalies. These include underreaction and limited attention induced by information asymmetry, as well as speculative demand driven by retail investors' herding behavior in equity markets. Compared to international studies, existing Chinese research predominantly focuses on measuring and comparing tail risk metrics, with limited exploration of tail risk's role in asset pricing. Notably, the significant negative correlation between left-tail risk and returns documented in U.S. equities by Atilgan et al. (2020) [2] remains underexplored in China—a critical research gap this study addresses.

China's stock market, emerging in 1990, exhibits distinct structural features compared to the intricate U.S. market, including lower market efficiency, divergent risk spillover dynamics, and a retail-dominated investor base with exceptionally high turnover rates. These characteristics render direct extrapolation of international findings inappropriate, necessitating localized explanatory frameworks. This paper investigates two pivotal questions:

① Does a left-tail risk anomaly exist in China's A-share market?

② Can behavioral finance mechanisms explain its formation?

2. Literature Review

2.1. Studies Related to Left Tail Risk

Left-tail risk refers to the risk of a rare negative event occurring, and it is the left-tail risk metric that is the explanatory variable in this study. The use of value-at-risk (VaR) as a measure of left-tail risk was first introduced by J.P. Morgan, and because it is easy to understand and easy to explain, it has been used as an important tool for measuring financial risk not only in academia, but also in analytical organizations such as stock exchanges. At-risk value refers to the maximum possible loss of an asset under a certain level of confidence over a certain period of time. With the deepening of research, scholars calculate the value-at-risk based on Markowitz's portfolio theory, using the common combination of variance and covariance.This is in contrast to Dowd's study in 1999, which first constructs a succinct extreme value model based on the premise of finite thresholds in which the value at risk is taken into account at a certain confidence level[3]. Considering the uniform property of various financial assets, i.e., sharp peaks and thick tails, Christoffersen and Errunza estimated it with GARCH and EGARCH models in their 2000 study[4]. The superiority of value-at-risk led Campbel et al. to introduce VaR into portfolio selection and asset pricing models in their 2001 study[5].Pritsker, on the other hand, proposed to use the FH approach to improve the generally applicable historical simulation methods based on computational methodological considerations in his 2001 study[6]. The strict assumptions of the model often limit its performance ability, combined with the excellent application of machine learning and other methods among nonlinear attributes, later scholars incorporated neural network models and GARCH models to improve the nonparametric estimation methods, which simplified and improved the computational process and efficiency of the original multivariate investor portfolios. Based on the need for tail correlation and extreme risk, CoVaR is often used to capture valid but missing paths under the estimation of VaR methods. Currently, the CoVaR model is the more widely used model in the literature. In an empirical study, Selmi et al. used CoVaR metrics and found that oil portfolios under a combination of multiple financial submarkets can reduce the effectiveness of overall stabilization risk[7]. The following metrics have all been widely used in the ongoing development process, including Value at Risk (VaR), Marginal Expectation Shortfall (MES), Systematic Expectation Shortfall (SES), Conditional Value at Risk (CoVaR), Systematic Risk Scale (SRISK), and Catastrophic Risk in Financial Firms (CATFIN).

2.2. Related Research on Asset Pricing

Left-tail risk refers to the risk of a rare negative event occurring, Starting from the earliest mean and variance theory, which converts investment returns into a linearly constrained problem under a specific function, what determines the cross-sectional stock returns becomes the focus of scholars' research[8], with the Capital Asset Pricing Model (CAPM) being the most common[9, 10]. It describes a positive linear channel for investors to assess the relationship between systematic risk and asset returns that cannot be diversified through a portfolio. Domestic scholars Chen Yuan and Yan Haibo use the CAPM model to calculate the market risk premium coefficient and test the correlation between stock returns and market risk[11]. While the set of Fama and MacBeth in 1973 in the study was systematically summarized after the famous Fama-MacBeth regression method[12], and based on this method to explore the relationship between the degree of risk premium and expected return volatility in the U.S. stock market, the subsequent analysis of this paper is also the use of this regression method.

With the continuous enrichment of empirical research methods, scholars have improved both in terms of introducing new risk indicators and empirically testing the applicability. Within the original framework, Qin added market investors' regret to the CAPM model in his 2020 study to examine the cross-sectional moderating effect of regret premium on the risk-return relationship[9]. When investors adjust their portfolios, the asset pricing model can misbehave, which highly introduces the possibility of undervaluing assets, as found in Horenstein's 2020 study[10]. Inspired by the insignificant applicability of the model, new arbitrage-free pricing models (APT) emerged. However, the traditional asset pricing model cannot explain the cross-sectional variation of average stock returns[13], based on which, in order to better explain the average stock returns, scholars start to explore the new factors by incorporating new factors and constructing them with market characteristics.

Within the framework of the efficient market hypothesis theory, macroeconomic variables and firm-specific risk factors became the two main categories of variables in empirical studies.Fama and French first extended the traditional asset pricing model with firm-specific risk indicators, i.e., firm size and firm value, in their 1993 study, and the three-factor model was born, and has always served as the root to guide subsequent asset pricing studies[14]. Due to the failure to consider the upper and lower bounds of profitability and investment and financing of enterprises in operation, Novy-Marx rejected the three-factor model in the study of 2013[15], and Fama and French then continued to improve it in the study of 2015, and finally confirmed the validity of the five-factor model with empirical evidence[16]. During this period of optimization of the model, many scholars have made contributions: momentum factor, liquidity factor, etc. were introduced, but most of them have come to the conclusion that the anomalous conclusion of "risk is proportional to the return" is contrary to the mature model of asset pricing has always been stuck in the five-factor model and has not been substantially advanced. In the face of this "low-risk anomaly", domestic scholars have also launched a large number of studies on asset pricing. Li and Jin and Li Zhan in 2000 study based on the Shanghai and Shenzhen market empirical evidence that the positive correlation of the stock market has a nonlinear characteristic outside the CAPM model[17], so Deng Kobin and Zeng Hai-ship in 2014 study will focus on financing constraints, in the microenterprise perspective will be identified as a proxy variable for systematic risk, and concluded that the stock return has a positive driving force[18]. While Hu et al. in their 2021 study took a different approach and chose to introduce accounting information relevance indicators into the five-factor model, starting from improving the stock selection ability to help investors improve their decision-making efficiency[19].

2.3. A Review of Related Research on Left-Tail Risk and Asset Pricing

This paper does not focus on how to measure the left-tail risk, but chooses the robust indicator that has been tested in several papers, i.e., the explanatory variables derived from the most representative backtracking simulation calculation method as the basis of the subsequent analysis. In recent years, foreign scholars have been paying more and more attention to the relationship between left-tail risk and stock returns, and the main research results are still focused on systematic tailwind risk, but foreign scholars have proposed that the predictive perspective of individual stocks' left-tail risk on their future returns is rarely researched domestically. As there are many retail investors in the Chinese stock market, investors are more prone to irrational behaviors, thus enriching the research on the relationship between left-tail risk and future stock returns is of practical significance and feasible for implementation.

In recent decades, the interdependence between asset risk and return, i.e., the asset pricing problem, has always been an important direction of financial theory and empirical research, especially after the emergence of multifactor models. In terms of the overall research development process, most of the pricing factors are proposed by foreign scholars, and domestic scholars are mostly to test the applicability of submarkets, with the rise of behavioral finance, domestic scholars is to understand the pricing factors on the innovation, such as investors due to information asymmetry brought about by the response to the lack of and limited attention to the retail investor's blindly follow the psychology of the stock market investment in the betting-type demand and other behaviors. Based on this, this paper follows the traditional research idea of asset pricing, differentiates the application effect of different market themes, and selects the latest company characteristic index to test whether the left-tailed momentum exists in the Chinese market, and interprets the performance of the company characteristic index on the left-tailed momentum from the perspective of behavioral finance.

3. Description of Data and Research Methods

3.1. Research data and variables

In this paper, we study the monthly returns of all A-shares listed on the Shanghai Stock Exchange and Shenzhen Stock Exchange, with the study interval from January 1, 2000 to December 31, 2022, and the data are mainly obtained from the Cathay Pacific database (CSMAR). Considering the special phenomena in the Chinese market, such as speculation in IPOs, ST stocks, shells, etc., in order to avoid abnormal returns due to these phenomena, we further screen the stocks based on the criteria adopted in the existing literature [36-38], which include the following: (1) the listing should be for 6 months; (2) being suspended from trading for less than 5 trading days in the past month; (3) being suspended from trading for less than 120 trading days; (4) no suspension on the portfolio construction or rebalance (re-balance) day; (5) non-ST or ST* stocks; and (6) no one-word up or down stops on the portfolio construction or rebalance (re-balance) day.

The core explanatory variable in this paper is left-tailed momentum, which is measured primarily by the Value at Risk (VaR) and Expected Shortfall (ES) of individual stock returns,that is, it is expressed as the maximum possible loss of a certain asset at a certain confidence level $1-\alpha$ in a certain period Δt. Given a fixed period of one month, VaR measures the likelihood of incurring a loss in the immediately following month when the probability is given. Drawing on the approach used by Baliz in his 2009 study, this paper will use backtracking simulation to calculate the value-at-risk, and while being consistent in terms of proportionality, this paper will select data on a month-to-month scale to make it easy to visualize the changes in the time series, and thus, assuming that the starting time falls at the end of the month, monthly adjusted returns on individual stocks will be used from month $t-11$ to month t (a total of 12 months), and the Based on this, the VaR of the individual stocks will be calculated, and since there is some probability that the maximum possible loss will be negative, the returns will be multiplied to obtain a positive loss magnitude, which can be easily interpreted in an intuitive way, i.e., as the value of the VaR increases, the higher the left-tail risk is. Considering the occurrence of anomalies, it is generally required that individual stocks have a sample size of not less than 10 months in the corresponding time period, and all of the above applies to both the value at risk and the expected value of losses.

At the macro level, the risk-return anomaly is easily created by considering the potential interaction between left-tailed risk and future stock returns, i.e., the relationship is mediated by certain firm characteristics, e.g., a certain firm characteristic reverses or counteracts the negative relationship that exists between left-tailed risk and cross-sectional stock future returns. At the micro level, the distribution of returns on the left-hand side represents losses and risks, and there is a momentum effect, i.e., the larger the left-hand side returns, the better the future performance of the firms, and the smaller the left-hand side returns, the worse the future performance of the firms. In the Chinese market, the empirical findings of Zhen et al. in 2020 and Wang et al. in 2022 contradict this phenomenon, i.e., the higher the left-tail risk, the lower the return in the Chinese market. The Chinese stock market always shows two forms, one is the growing scale of listed companies, up to now there are more than 4,000 companies, its expansion rate reaches the result of the U.S. stock market's 200 years of development; the other is the expanding retail investor group, the Shanghai and Shenzhen markets with positive volatility in the long-term perspective, which all highlight the upward force of the Chinese stock market. More importantly, China's stock market is susceptible to policy direction, major external events, and carries a large amount of asymmetric sentiment, and irrational markets are brewing to become the next risk aggregation point under sudden rises and falls. Therefore, the left-tailed momentum effect is more obvious in stocks with a large proportion of retail investors, stocks that receive less attention from investors, small caps and other stock groups, and there is no momentum effect in the Chinese market, but there is a significant reversal effect is a Chinese-style stock market characteristic that is worth exploring. Combining the above perspectives, this paper will consider the following control variables to explore the direction of the correlation and the strength of the correlation between left-tailed momentum and stock returns under the Chinese market: analyst coverage (*FirmAtt*), institutional investor shareholding ratio (*HoldPro*), book-to-market ratio (*BM*), firm size (*Size*), market beta (*Beta*), short-term inversion (*STR*), illiquidity indicator (*Illiq*), conditional skewness (*Coskew*), downside beta (*Betadown*), idiosyncratic volatility (*Ivol*), "lottery" stock preference (*Maxavg*), average turnover (*Avg*) and abnormal turnover (*Abn*).

Analyst Coverage Data (*FirmAtt*) records how many analysts of each listed company are tracked and studied by the analysts of securities companies; Institutional Investor Shareholding Percentage (*HoldPro*) data from the annual financial results, the data records the proportion of institutional investors for each listed company's shareholding; Book-to-Market Ratio (*BM*) data from the latest release of the financial results of the latest end of the month, the latest ratio of book-to-market ratio, i.e., the book value divided by the company's market capitalization; Company Size (*Size*) data from the same source as above, for each month-end closing price multiplied by the number of all shares listed and issued by the company at the end of the month, and then take the logarithmic value of the value, to facilitate the reduction of the impact of outliers, more closely to the normal distribution; market beta (*Beta*), at the end of each month at the point in time, the use of the past 250 trading days as a window (requires no less than 200 trading days of data), based on the CAPM model regression, to obtain the individual stock Beta; Short-term reversal (*STR*), i.e., the return of the last 1 month, at each month-end time point to calculate the return of individual stocks in the current month, which reflects the reversal effect of the Chinese market; Illiquidity indicator (*Illiq*), at each month-end, to calculate the Amihud illiquidity indicator of individual stocks for the current month; Conditional skewness (*Coskew*), at each month-end, to calculate the return of the individual stocks in the past 12 months in the regression model of individual stock's excess return on the market factor and the coefficient of market factor squared in a regression model of market factor squared; downside beta (*Betadown*). At the end of each month, calculate the covariance between the individual stock's excess return and the market's excess return divided by the variance of the market's excess return when the market's excess return is lower than its average excess return over the past 12-month interval; idiosyncratic volatility (*Ivol*), at the end of each month, use the daily returns of the past 12 months, regress them based on the CH3 model, obtain the residuals, and calculate their standard deviation as the individual stock's idiosyncratic volatility; "lottery" stock preference (*Maxavg*), at the end of each month, the average of the five highest daily returns in the month is calculated as a measure of "lottery" stock preference; average turnover (*Avg*) and abnormal turnover (*Abn*), the daily turnover of a stock is equal to the number of shares actually traded divided by the number of shares actually traded. Equal to the actual number of shares traded divided by the total number of shares available to obtain the total turnover rate. At the end of each month after the total turnover rate is obtained, the average turnover rate for each trading day of the month is calculated and divided by the total turnover rate, i.e., the abnormal turnover rate.

Table 1. Summary of variables

Variable type	Variable name	Variable symbol	Description of variables
Explanatory variable	At-risk value	*VaR*	Measuring left-tailed risk with backtracking simulations
	Expectation loss	*ES*	
Control variable	Analyst Coverage	*FirmAtt*	Recorded how many analysts from securities firms follow each listed company
	Institutional investor shareholding	*HoldPro*	Shareholding of institutional investors
	Book-to-market ratio	*BM*	Carrying value divided by the market capitalization of the company
	Company size	*Size*	Logarized monthly individual stock market capitalization
	Market beta	*Beta*	Market Premium Factors for CAPM Models
	Short term reversal	*STR*	Monthly market reversal effect
	Non-mobility indicators	*Illiq*	Ratio of absolute value of daily individual stock return considering reinvestment of cash dividends to daily individual stock trading volume
	Conditional skewness	*Coskew*	Individual stock excess returns over the past 12 months are regressed on the market factor and the market factor squared, yielding the slope coefficient of the market factor squared
	Downside beta	*Betadow*	Construct the division of the covariance between the individual stock's excess return and the market's excess return and the variance of the market's excess return if the market's excess return is lower than its average excess return over the past 12 months
	Idiosyncratic volatility	*Ivol*	Standard deviation of residuals from regression model CH3
	"Lottery"stock preferences	*Maxavg*	Average of the 5 highest daily returns of the month
	Average exchange rate	*Avg*	At the end of each month, calculate the average daily turnover rate of the individual stock for the past 250 trading days
	Abnormal exchange rate	*Abn*	Frequency of trading in a stock during the month

3.2. Empirical method

The empirical methods used in this paper are the portfolio spread method and the Fama-MacBeth regression method. Assuming a sample period $t = 1, 2, \ldots, T$, at the end of the month t , an indicator is first ranked and grouped, and then the bivariate portfolios are obtained by repeating the grouping procedure while controlling for the first grouping variable. The goal of multivariate portfolio analysis is to examine the relationship between two or more variables in the cross-section, and to examine stock price returns with a one-month lag through the current month's left-tailed stock risk indicators and related firm characteristics, i.e., to examine the predictive power of future stock returns from a multidimensional perspective. Its advantage lies in the nonparametric study, which is not bound to the assumption of a strict linear relationship and is usually better suited to test the nonlinear relationship between multiple variables. However, the limitation of cross-sectional analysis is the lack of marginal change studies between explanatory and interpreted variables. Therefore, this paper will also use Fama-MacBeth regressions to sequentially test the relationship between different firm characteristic indicators and left-tailed risk and future returns, and compare the results with the inclusion of both risk indicators and firm characteristic indicators in the model, in order to explore the marginal contribution of the explanatory and control variables to stock returns.

3.2.1. Portfolio analysis method

In order to test the relationship between VaR (left-tailed risk) and future stock returns, we first use univariate portfolio analysis. The three steps are as follows: ① Based on the sorting, the stock return series are divided into 10 groups, which are D1, D2, D3, D4, D5, D6, D7, D8, D9, and D10, where D1 is the stock portfolio with the largest left-tailed risk, and D10 is the one with the smallest left-tailed risk; ② In the time series, the monthly average return of each stock portfolio for the next month is calculated based on the left-tailed risk; ③ analyze whether there is a correlation with the stock's return in the coming month. In addition, in order to test whether the average return of the largest and smallest difference portfolios in the monthly dimension can be explained by the market risk premium factor, size factor, market factor, value factor, and turnover factor proposed by Liu et al, i.e., by the CAPM model, CH3 model, and CH4 model, respectively, at this point, the statistic t adapted by Newey-western is used. If the statistic t is greater than or equal to 1.96, it means that the results are significant at the 5% level. The difference portfolio is denoted as "L-S", and if its alpha value fails the test t , it means that there is a significant correlation between VaR and stock future returns and the results are robust.

The next step is bivariate portfolio analysis, i.e., grouping firm characteristics and left-tailed risk indicators at the same time. The key is to expand the influencing factors to two, i.e., whether the correlation between left-tailed risk and cross-sectional stock returns changes when the firm characteristics indicators come first, i.e., it can be interpreted as the moderating effect of the firm characteristics indicators on the relationship between them. The specific steps are as follows: ① At the beginning of t , stocks are equally divided into 10 groups based on a certain characteristic variable at the end of month $t-1$, which are recorded as groups H1, H2, H3, H4, H5, H6, H7, H8, H9 and H10 in descending order, and then equally divided into 10 groups by VaR value within each group, which should be ultimately in the 10×10 stock portfolios formed at the beginning of t as a result; ② Calculate separately the monthly average return; ③ VaR grouping as a benchmark, merging each company characteristic variables, that is, in the operation expressed as the calculation of the average value of the portfolio return on the time series.As with the univariate grouping analysis, it is still necessary to test whether the alpha value of the difference portfolio passes the t -test to explore the robustness of this correlation.

3.2.2. Fama-MacBeth returns

IFor the limitations of the portfolio analysis method, Fama and MacBeth proposed a new regression method, Fama-MacBeth regression[12], which is widely used in econometrically panel data studies because the model estimator it obtains possesses the excellent property of being unbiased. In the field of financial research it is mainly used to estimate factor exposures and risk premiums in models.

In this paper, we use Fama-MacBeth regression to control for multiple firm characteristics simultaneously in order to test the predictive ability of VaR on stock returns in the cross-section. The specific steps are as follows:①in each month, individual firm characteristics and left-tailed risk are sequentially regressed on future stock returns; ② all firm characteristics and left-tailed risk are regressed on future stock returns; and ③ the coefficients of the regression model are extracted and averaged for each month, and then the model regression results are evaluated using the Newey-west adjusted values. In order to avoid the effect of outliers, all variables were regressed at 1% and 99% quantile levels with shrinkage. The specific regression equations are as follows:

$$\begin{aligned} R_{i,t+1} &= \beta_{0,t} + \beta_{1,t} VaR_{i,t} + \beta_{2,t} FirmAtt_{i,t} + \beta_{3,t} HoldPro_{i,t} + \beta_{4,t} BM_{i,t} + \beta_{5,t} Size_{i,t} + \beta_{6,t} Beta_{i,t} \\ &+ \beta_{7,t} STR_{i,t} + \beta_{8,t} Illiq_{i,t} + \beta_{9,t} Coskew_{i,t} + \beta_{10,t} Betadown_{i,t} + \beta_{11,t} Ivol_{i,t} \\ &+ \beta_{12,t} Maxavg_{i,t} + \beta_{13,t} Avg_{i,t} + \beta_{14,t} Abn_{i,t} + \varepsilon_{i,t+1} \end{aligned}$$

where $R_{i,t}$ is Stock i 's average return in month $t+1$, $VaR_{i,t}$ is Stock i 's left-tailed value-at-risk in month t , $firm\_AnaAttention_{i,t}$ is Stock i 's number of analyst coverage in month t , $details\_HoldProportion_{i,t}$ is Stock i 's institutional investor ownership in month t , $BM_{i,t}$ is Stock i 's book-to-market ratio in month t , $Size_{i,t}$ is Stock i 's firm size in month t , $Beta_{i,t}$ is Stock i 's market beta in month t , $STR_{i,t}$ is Stock i 's short-term reversal in month t , $Illiq_{i,t}$ is Stock i 's illiquidity indicator in month t , $Coskew_{i,t}$ is Stock i 's conditional skewness in month t , $Betadown_{i,t}$ is Stock i

's downside beta in month t, $Ivol_{i,t}$ is Stock i 's idiosyncratic volatility in month t, $Maxavg_{i,t}$ is Stock i 's "lottery ticket" stock preference in month t, $Avg_{i,t}$ is Stock i 's average turnover rate in month t, and $Abn_{i,t}$ is Stock i 's abnormal turnover rate in month t.

4. Analysis of Left-tailed Risk and Future Stock Returns

4.1. Univariate portfolio analysis (UPA)

In this section, we will first explore the use of VaR to inscribe left-tail risk by considering the different performance of portfolio returns under different left-tail risks. Tables 2 and 3 show the raw and multifactor model-adjusted portfolio returns under equal-weighted market capitalization average as well as weighted market capitalization average portfolios for the entire sample period from January 1, 2000 to December 31, 2022, respectively. Under the equal weighted market capitalization average portfolio, a gradual downward trend in portfolio returns can be observed as the left-tailed risk continues to increase. group D1 is the portfolio with the highest left-tailed risk with an average return of 0.5%, group D10 is the portfolio with the lowest left-tailed risk with an average return of 1.03%, and the group L-S has an average return of -0.52%, with a t-statistic of -1.98, which at the 5% level which is statistically significant. However, the average return of the L-S group on the factor model-adjusted alpha value is statistically significant only at the 10% level. Moreover, under the inverse growth of risk and return, as the left-tailed risk is about to reach its nadir, the return instead shows a small decline rather than a sustained increase, with or without the inclusion of the market factor in the adjustment of the return. Under the weighted market capitalization average portfolio, the same situation exists between the D9 and D10 portfolios similar to that of equal weighting, with the difference that at this point the correlation between the original portfolio return series and the CAPM model-adjusted returns and left-tail risk is not statistically significant at the 10% level, while the portfolio returns adjusted by the three-factor model have significantly higher explanatory power compared to equal weighting. It is statistically significant at the 5% level. This shows that there exists a certain degree of left-tailed risk anomaly in the Chinese market, i.e., there is a significant negative correlation between the portfolio return and the left-tailed risk of a stock, and the relationship between the average portfolio return and the left-tailed risk adjusted by the four-factor model is more robust, whereas the traditional CAPM and the three-factor model have a certain weakening effect on this relationship. Under the weighted market capitalization average portfolio, as stocks with large market capitalization weights are considered, the above results also side-step the fact that left-tailed momentum is more likely to be found in small-cap samples.

4.2. Average portfolio characterization

Table 2. Portfolio returns for univariate groupings based on VaR groupings

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	L-S
Panel A: Equal Weighted Market Capitalization Average Portfolio											
Raw	0.005	0.0068	0.0083	0.0088	0.0098	0.0103	0.0108	0.0112	0.0113	0.0103	-0.0052
	(0.7961)	(1.081)	(1.2998)	(1.4055)	(1.5956)	(1.6752)	(1.7512)	(1.8281)	(1.8873)	(1.8626)	(-1.9868)
CAPM	0.0039	0.0056	0.0071	0.0077	0.0085	0.0091	0.0095	0.0098	0.0099	0.0089	-0.0049
	(0.7106)	(1.0167)	(1.3141)	(1.4273)	(1.6427)	(1.736)	(1.8311)	(1.9483)	(2.0352)	(2.0037)	(-1.8804)
CH3	-0.0002	0.0014	0.0037	0.0043	0.0054	0.0061	0.0061	0.0066	0.0074	0.0058	-0.0061
	(-0.036)	(0.2419)	(0.6125)	(0.6906)	(0.9042)	(1.0474)	(1.0535)	(1.1897)	(1.3889)	(1.2206)	(-1.9176)
CH4	0.0018	0.0035	0.0059	0.0063	0.0076	0.0084	0.0084	0.0087	0.0098	0.0081	-0.0063
	(0.294)	(0.5808)	(0.9843)	(1.0557)	(1.3074)	(1.4973)	(1.4929)	(1.6332)	(1.9074)	(1.7689)	(-1.9739)
Panel B: Weighted Market Capitalization Average Portfolio											
	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	L-S
Raw	0.0009	0.0015	0.0041	0.003	0.0048	0.0056	0.0059	0.0068	0.0076	0.0069	-0.0059
	(0.1496)	(0.2534)	(0.6498)	(0.5071)	(0.8255)	(0.9308)	(1.0068)	(1.1776)	(1.3659)	(1.3592)	(-1.6087)
CAPM	0.0001	0.0008	0.0032	0.0019	0.0037	0.0044	0.0048	0.0056	0.0063	0.0058	-0.0057
	(0.0202)	(0.1487)	(0.591)	(0.3871)	(0.7407)	(0.8669)	(0.943)	(1.1431)	(1.3755)	(1.3245)	(-1.5427)
CH3	-0.0049	-0.0027	-0.0001	-0.0006	0.0006	0.0019	0.0022	0.0032	0.0062	0.0042	-0.0092
	(-0.7974)	(-0.4534)	(-0.0297)	(-0.1072)	(0.1233)	(0.3499)	(0.3672)	(0.5895)	(1.126)	(0.8481)	(-2.374)
CH4	-0.0027	-0.0007	0.0016	0.0012	0.0026	0.0042	0.0035	0.0049	0.0086	0.0067	-0.0094
	(-0.4471)	(-0.1342)	(0.276)	(0.222)	(0.5084)	(0.7875)	(0.6179)	(0.9354)	(1.6585)	(1.3981)	(-2.3677)

Note: (1) The first row in each category corresponds to the alpha value and the t-value in the second row (). (2) The first category refers to the original portfolio returns, and the rest are the portfolio returns adjusted by the CAPM model, CH3 model, and CH4 model, respectively.

Next, we will examine which firm characteristic indicators can act as reasonable explanatory factors between risk and return. In the data processing section, the univariate grouping described above is followed by averaging the firm characteristic indicators for each left-tailed risk dimension. Table 4-2 shows the portfolio characteristics grouped based on the left-tailed risk measured by VaR .The average VaR value of group D1 is 9.71%, which implies that the highest risky portfolio has a daily return sorted by the 1% quartile equal to -9.71% over the past year, and similarly the lowest risky group, D10, is 4.88%, which implies that the result of the sorted by the 1% of the daily return is -4.88%. Next, we see that analyst coverage stays in the same direction as left-tail risk decreases, which shows that stocks with higher left-tail risk are responsive to analyst coverage, but it is also important to note that when left-tail risk is high, analyst coverage may produce a wait-and-see period, i.e., the phase from group D2 to D4. Conversely, institutional investor holdings are inversely expressed, i.e., stocks of companies with higher left-tailed risk tend to have a larger proportion of large institutional holdings. At the same time, some stocks with lower left-tailed risk usually exhibit higher company size and higher book-to-market, i.e., the company as a whole performs well on the fundamentals. For the reversal effect, as left-tail risk declines, the reversal effect is highly cyclical or "seesaw", while left-tail risk always maintains a positive feedback relationship with market premiums and illiquidity indicators. The relationship between left-tailed risk is completely opposite when acting on abnormal turnover and average turnover, i.e., abnormal turnover is more prominent in stocks with higher left-tailed risk, and stocks with higher left-tailed risk tend to have higher idiosyncratic risk and lower betting attributes. The above characteristics are similar in the equal-weighted market capitalization average portfolio and the weighted market capitalization average portfolio.

Combined with several studies in the current literature, the firm characteristics indicators selected in this paper help to understand the return contribution on the stock cross-section. That is, lower analyst coverage levels, lower firm size-to-book-to-market capitalization ratios, higher values of $Beta$, higher illiquidity metrics, higher downside beta, higher idiosyncratic volatility, higher gaming attributes, and higher abnormal turnover rates are typically associated with better expected stock return performance. Therefore, we will further examine cross-sectional effects through bivariate groupings and marginal contributions in the cross-section through Fama-MacBeth regressions.

Table 3. VaR -based combination characterization results

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Panel A: Equal Weighted Market Capitalization Average Portfolio										
VaR	0.0971	0.0895	0.0838	0.0790	0.0748	0.0711	0.0675	0.0637	0.0589	0.0488
HoldPro	0.9790	0.9637	1.0335	1.0200	0.9890	0.9548	0.9024	0.8335	0.8046	0.6372
FirmAtt	3.5544	3.9635	4.3046	4.8919	5.0540	5.5208	5.7593	6.3618	7.3214	9.7072
BM	0.3482	0.3694	0.3851	0.3996	0.4135	0.4297	0.4484	0.4709	0.5020	0.6600
Size	15.0581	15.0706	15.0993	15.1582	15.1812	15.2383	15.2817	15.3795	15.5289	16.0273
Beta	1.2834	1.2700	1.2460	1.2227	1.1903	1.1566	1.1197	1.0752	1.0082	0.8520
STR	0.5205	0.7203	0.6919	1.0083	0.4265	0.3873	0.4150	1.1723	0.5629	0.8427
Illiq	0.2678	0.1761	0.1828	0.1829	0.1851	0.1833	0.1790	0.1674	0.1678	0.1780
Coskew	-4.3745	-4.0826	-3.8137	-3.4996	-3.1649	-2.7142	-2.4574	-1.8978	-1.3392	-0.0250
Betadown	1.4167	1.4003	1.3615	1.3445	1.2943	1.2512	1.2056	1.1452	1.0676	0.8601
Ivol	0.4610	0.4117	0.3907	0.3720	0.3569	0.3434	0.3283	0.3117	0.2916	0.2574
Maxavg	0.0390	0.0374	0.0363	0.0352	0.0343	0.0335	0.0326	0.0315	0.0297	0.0259
Avg	2.0977	1.8793	1.7085	1.5438	1.4288	1.3380	1.2241	1.1034	0.9538	0.6984
Abn	1.0223	1.0282	1.0361	1.0479	1.0517	1.0623	1.0674	1.0792	1.0819	1.0868
Panel B: Weighted Market Capitalization Average Portfolio										
	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
VaR	0.0970	0.0894	0.0838	0.0790	0.0748	0.0711	0.0675	0.0637	0.0588	0.0448
HoldPro	0.6505	0.5874	0.5858	0.5710	0.5718	0.5060	0.5056	0.4949	0.4380	0.2929
FirmAtt	7.0814	7.8813	9.0152	10.9027	11.0029	12.3579	12.9008	14.5465	16.6293	19.6601
BM	0.3382	0.3667	0.3798	0.3974	0.4123	0.4182	0.4448	0.4843	0.5221	0.8342
Size	15.8017	15.8680	15.9976	16.1930	16.2134	16.3367	16.4274	16.6959	17.0884	18.4171
Beta	1.0658	1.1724	1.1711	1.1815	1.1508	1.1128	1.0786	1.0427	0.9794	0.7432
STR	0.5535	0.8838	0.7517	0.9327	0.4409	0.4203	0.3716	1.1741	0.5124	0.8669
Illiq	0.1260	0.1230	0.1227	0.1177	0.1147	0.1113	0.1056	0.0906	0.0784	0.0539
Coskew	-2.6239	-2.4907	-2.2166	-1.8441	-1.4610	-1.2180	-0.8644	-0.2620	0.4806	1.9606
Betadown	0.4215	0.4912	0.5194	0.5268	0.5126	0.4872	0.4872	0.4761	0.4570	0.3525
Ivol	0.3773	0.3785	0.3554	0.3484	0.3373	0.3232	0.3099	0.2933	0.2692	0.2085
Maxavg	0.0397	0.0379	0.0369	0.0356	0.0347	0.0340	0.0330	0.0316	0.0296	0.0231
Avg	1.8087	1.6277	1.4553	1.2682	1.1748	1.0886	0.9823	0.8468	0.6944	0.3568
Abn	1.0168	1.0232	1.0330	1.0503	1.0545	1.0587	1.0648	1.0686	1.0647	1.0484

4.3. Bivariate portfolio analysis (BPA)

We show a table of portfolio returns and their portfolio returns adjusted by the traditional asset pricing model, the three-factor model, and the four-factor model, when all firm characteristics are individually used as the first grouping basis in turn and averaged over the time series under the second grouping basis. The results show that when controlling for the market beta index, when grouped as a left-tailed risk measure, the returns are statistically significant at the 5% level both in the original model and adjusted by the multifactor model, but when going into market capitalization weighting, the explanatory power of the three-factor model and the four-factor model rises, but the portfolio returns from the original return portfolios and from the traditional capital asset pricing model maintain the original explanatory strength. Controlling for market beta performs similarly. When controlling for the feature of conditional skewness, the return explanatory power of the market capitalization-weighted portfolios is weaker than that of the equal-weighted market capitalization, except for the four-factor model. And when controlling for the illiquidity metric, the multifactor model adjusted portfolio return reporting underperforms, which is exacerbated by the weighted market capitalization portfolio. Traditional asset pricing models are usually set based on a completely idealized state of the market, i.e., without any friction, while investors are completely rational persons, i.e., free from any betting speculative psychology, contagious information in the market, etc. However, in the reality of the stock market where information is severely asymmetric, the process of participating in a transaction has to be done in such a way as to accurately allocate "eggs However, in the real stock market with serious information asymmetry, it is unrealistic to accurately allocate the "eggs" in order to maximize the return. From another perspective, this means that under the traditional perception of "risk and reward are directly proportional", i.e., when higher risk compensation is required under high risk, the idiosyncratic risk has also become an important risk element of the risk-return, and thus has the ability to influence the pricing of the assets. Ability to influence asset pricing.

While the idiosyncratic volatility usually represents information unrelated to the market face pricing factors, the results in the table show that under the equally weighted market capitalization portfolios, none of the idiosyncratic risk volatility of the L-S group passes the t-test, and only when the market capitalization-weighted portfolios, the average return after conditioning with the three-factor and the four-factor models is statistically significant at the 1% level, i.e., information unrelated to market pricing facets has no significant effect in the examination of the left-tailed risk and return-return The role of performance between is insignificant, but there is a significant confounding effect when the market capitalization factor is moderated. The characteristic of firm size is consistently a significant indicator of the performance of left-tailed risk and stock returns, and is a strong risk factor in both equal-weighted market capitalization and weighted market capitalization portfolios. When controlling for betting stock preferences, the relationship between left-tailed risk and portfolio returns is insignificant, and a negative correlation at the 5% confidence level is obtained only under market capitalization weighting and after adjusting for the three- and four-factor models. The difference is that the inversion effect in the negative correlation between the two significant through, general risk and return should show a positive correlation between the left-tailed risk explored in this paper is actually also a kind of inversion effect, and this inversion effect is different from the same, abnormal turnover rate and downside beta the same reason. Behavioral finance is an important theoretical support for investors' decision-making returns in the financial market, and the attention and processing capacity of market participants are limited. The two indicators of institutional investor shareholding and analyst coverage serve as important indicator variables for investors' delayed reaction to bad (good) information, and the results show that the phenomenon of left-tailed risk is more pronounced in stocks with low retail shareholding and analyst attention. Overall, most of the left-tailed risk phenomena cannot be explained by the traditional asset pricing model factors, but the explanatory power is improved by the three-factor and the four-factor model that introduces the momentum factor, with the four-factor model being superior. And it is a direction to consider the left-tailed risk indicator as a new pricing factor in the Chinese stock market.

4.4. Fama-MacBeth regression analysis

In order to examine the marginal contribution of left-tailed risk to the next month's stock returns, as well as to take the various firm characteristics into account for the marginal correlation, we conducted Fama-MacBeth regressions, sequentially regressing the left-tailed risk on individual firm characteristics, as well as regressing the entire set of firm characteristics and the left-tailed risk together in the model. First, regardless of the explanatory variables included into the model, it can be seen that the coefficient of left-tailed risk varies between -0.04 and -0.06, always maintaining a negative correlation. Next, the negative cross-sectional correlation between risk and return expressed in model (1) is not significant, but when controlling for firm characteristics, i.e., from model (2) to model (14), the model is statistically significant at the 5% and 10% levels only when market beta and downside beta are used as a single control variable, respectively, which seems to be echoed by the significant inversion effect in the Chinese stock market. This seems to echo the significant inversion effect in the Chinese stock market, whereas indicators such as firm size are consistently robust in the study of the risk-return relationship. When the model (15) controls for all firm characteristics, the relationship between left-tailed risk and cross-sectional returns becomes insignificant, at least in terms of predicting stock returns in the next month, probably because the effects of different types of indicators are somewhat hedged when firm characteristics are included, resulting in an offsetting effect. In summary, it is expected that firm characteristics have a reinforcing effect on the negative relationship between left-tailed risk and expected stock returns, but how to rationally categorize firm characteristics in order to reduce the possible conflict of effects and to highlight the reinforcing effect of characteristics on the negative correlation needs to be further investigated in the future.

4.5. Robustness check

In this section, we replace the measure of left-tail risk indicator by using the expected loss measure of the occurrence of tail risk, which is calculated by finding the average value of the loss for the past 250 trading days when the ordering of the daily returns of individual stocks is greater than the 99% confidence level. Tables 4-5 through 4-7 present the results of the univariate grouping analysis, the multivariate grouping analysis, and the Fama-MacBeth regression model, respectively. Due to space constraints, we only show the table of portfolio returns and their portfolio returns adjusted by the traditional asset pricing model, the three-factor model, and the four-factor model, using the downside beta, institutional investor ownership, and analyst coverage as the first grouping basis, and taking their time-series averages under the second grouping basis of VaR. In the univariate and bivariate grouping analysis, the strengthening effect between firm characteristics indicators and left-tailed anomalies is still present, especially in the higher institutional investor holdings and lower analysts' coverage where the negative correlation is statistically significant at the 1% level, and the rational explanation of behavioral finance will not be repeated here, and the coefficient of the expected loss in the regression model based on expected loss is still negative, keeping the left-tailed negative relationship between risk and stock's expected return in the next month, and all firm characteristics are statistically significant at the 5% level except for idiosyncratic risk volatility, betting stock preference, and abnormal turnover. In model (15), which incorporates all of the firm characteristics indicators regressed on expected loss versus expected return, the risk term is not significant, but the reversal effect and abnormal turnover rate exhibit strong significance whether alone or in working with other factors. Therefore, the negative correlation between left-tailed risk and expected stock returns persists with replacement of explanatory variables, and at this point the degree of explanation of the marginal contribution shows that the expected loss indicator is superior to the value-at-risk indicator.

Table 4. Results of *VaR* -based Fama-MacBeth regression

variant	1	2	3	4	5	7	6	8	9	10	11	12	13	14	15
Intercept	0.0104	0.0104	0.0133**	0.0074	0.0908***	0.0125*	0.0105*	0.0090	0.0134**	0.0123*	0.0149**	0.0166**	0.0092	0.0229***	0.0744***
	(1.6462)	(1.6506)	(2.1843)	(1.2697)	(3.7554)	(1.9591)	(1.6605)	(1.4235)	(2.1217)	(1.8444)	(2.2072)	(2.5913)	(1.4832)	(3.5175)	(2.6837)
VaR	-0.0452	-0.0452	-0.0686	-0.0371	-0.1658***	-0.0968*	-0.0459	-0.0621	-0.0846	-0.1253**	0.0296	0.0495	0.0070	-0.0513	-0.0643
	(-0.6830)	(-0.6859)	(-1.1977)	(-0.5765)	(-2.9136)	(-1.8060)	(-0.6999)	(-0.9636)	(-1.3925)	(-2.1260)	(0.4375)	(0.7509)	(0.1093)	(-0.7840)	(-1.1138)
HoldPro		0.0000													0.0001
		(0.0683)													(0.1856)
FirmAtt			0.0001												0.0003
			(0.3812)												(0.7945)
BM				0.0086***											0.0079**
				(2.6719)											(2.0544)
Size					-0.0044***										-0.0032*
					(-3.2094)										(-1.9181)
Beta						0.0021									0.0062
						(0.6049)									(1.0351)
STR							-0.0004*								-0.0006
							(-1.9320)								(-1.2986)
Illiq								0.0483***							0.1038***
								(2.8512)							(2.9986)
Coskew									-0.0006***						-0.0003
									(-3.0563)						(-0.9456)
Betadown										0.0052**					-0.0006
										(2.1619)					(-0.1472)
Ivol											-0.0284***				-0.0100
											(-4.9591)				(-0.8608)
Maxavg												-0.3639***			-0.1497*
												(-8.5949)			(-1.9128)
Avg													-0.0027***		-0.0032**
													(-3.4641)		(-2.0448)
Abn														-0.0113***	-0.0112***
														(-7.7914)	(-5.0890)
Adjust R^2	0.0216	0.0222	0.0338	0.0304	0.0491	0.0363	0.0273	0.0320	0.0296	0.0341	0.0281	0.0371	0.0288	0.0358	0.1252

Note: (1) Parentheses refer to the regression coefficient t -statistic, and asterisks from 1 to 3 refer to passing the test at the significance levels of 10%, 5%, and 1%, in that order.

Table 5. Results of *ES* -based Fama-MacBeth regression

variant	1	2	3	4	5	7	6	8	9	10	11	12	13	14	15
Intercept	0.0178***	0.0178***	0.0184***	0.0146**	0.0904***	0.0175***	0.0180***	0.0161***	0.0176***	0.0214**	0.0172 ***	0.0240***	0.0162***	0.0305***	0.0771***
	(2.9663)	(2.9687)	(2.8498)	(2.5840)	(3.7166)	(2.8696)	(2.9806)	(2.6371)	(2.9514)	(2.2382)	(2.7659)	(3.9372）	(2.7154)	(4.8027)	(2.8323)
VaR	-0.1003**	-0.1002**	-0.1012**	-0.0938**	-0.1557***	-0.1095**	-0.1020**	-0.1133**	-0.1056**	-0.2015**	0.0183	-0.0188	-0.0477	-0.1086**	-0.1114
	(-2.1921)	(-2.1972)	(-2.2674)	(-2.1731)	(-3.2587)	(-2.1661)	(-2.2466)	(-2.4925)	(-2.0768)	(-2.3061)	(0.3203)	(-0.4012）	(-1.1220)	(-2.3533)	(-1.3388)
HoldPro		0.0000													0.0001
		(0.0508)													(0.1889)
FirmAtt			0.0002												0.0004
			(0.6476)												(0.7933)
BM				0.0089***											0.0080**
				(2.7103)											(2.0660)
Size					-0.0043***										-0.0030*
					(-3.1356)										(-1.8275)
Beta						0.0009									0.0066
						(0.2415)									(1.0361)
STR							-0.0004*								-0.0007
							(-1.8218)								(-1.4038)
Illiq								0.0486***							0.1046***
								(2.8585)							(2.9931)
Coskew									-0.0005***						-0.0003
									(-2.8286)						(-0.9052)
Betadown										0.0054**					-0.0008
										(2.1022)					(-0.1990)
Ivol											-0.0284***				-0.0121
											(-5.2139)				(1.0300)
Maxavg												-0.3619***			-0.1517*
												(-8.5217)			(-1.9481)
Avg													-0.0031***		-0.0028*
													(-3.7663)		(-1.7918)
Abn														-0.0112***	-0.0109***
														(-7.6941)	(-5.1355)
Adjust R^2	0.0182	0.0187	0.0311	0.0271	0.0466	0.0341	0.0240	0.0286	0.0268	0.0329	0.0253	0.0342	0.0265	0.0326	0.1261

Note: (1) Parentheses refer to the regression coefficient t -statistic, and asterisks from 1 to 3 refer to passing the test at the significance levels of 10%, 5%, and 1%, in that order.

5. Conclusions and Outlook of The Study

This paper uses daily and monthly data from January 1, 2000 to December 31, 2022 in China's stock market, and proactively uses portfolio spread analysis and Fama-MacBeth regression in order to test the relationship between left-tailed risk and the future one-month return of stocks in China's stock market. The empirical results show that the monthly return difference between the highest left-tailed risk stock portfolio and the lowest left-tailed risk stock portfolio is -0.52%, and the Newey-west adjusted statistic is statistically significant at the 1% level, whereas the spread portfolio adjusted by the traditional capital asset pricing model is still significant, while the spread portfolio is still significant when adjusted by the three-factor model consisting of the market risk premium factor, the market capitalization factor, the book-to-market factor, and the momentum factor. factor model and the four-factor model with the addition of the momentum factor adjusted, are significant at the 1% level, the difference is that under the univariate grouping, the explanatory power of the model by the multifactor model is significantly prompted compared to the traditional capital asset pricing model model, but in the bivariate grouping controlling for the company's characteristic indexes, the significance difference is not much elevated but basically stays at the 1% level. At the same time, it can be seen that this phenomenon is more significant at lower institutional investor holdings and higher analyst coverage, i.e., contrary to the traditional concept of finance that "risk is positively correlated with return", the higher the left-tailed risky stocks, the lower the return in the future, and this anomaly is the left-tailed momentum.

The findings of this paper are of some academic significance. First, unlike theoretical studies on risk measures, this paper aims to empirically investigate whether there is a negative relationship between left-tailed risk and cross-sectional stock returns in the Chinese stock market, and to verify whether the left-tailed momentum that exists in the U.S. stock market exists significantly in the Chinese market where there are many retail investors. Secondly, this paper further explains this phenomenon from the perspective of investor underreaction in behavioral finance, pointing out the strengthening effect of institutional investors' shareholding ratio and analysts' coverage in the left-tailed momentum, and the findings of this paper enrich the related research results in the field of asset pricing and behavioral finance in China to a certain extent. At the same time, the findings of this paper can also provide reference for relevant government departments and investors. In recent decades, the frequent occurrence of "black swan" events has made investors pay more and more attention to the huge risk contagion chain behind the small probability events or extreme events, and at the same time prompted the relevant government departments that the tail risk may be a major threat to the smooth and orderly operation of the entire financial market system.

Although this paper empirically concludes that left-tailed momentum significantly exists in the Chinese stock market and that indicators reflecting investor concerns such as analyst coverage and institutional investor holdings have a significant strengthening effect, there are still areas worthy of improvement and refinement. First, this paper only uses a single left-tailed risk indicator, and there are a large number of reliable and effective measures in the current stock market, so we can try to horizontally compare the performance ability among different measures to test the effectiveness of different indicators on left-tailed risk. Second, although institutional investor holdings and analyst coverage can only be explained from the perspective of insufficient investor attention, and they tend to significantly strengthen the negative correlation of left-tailed momentum, but the inclusion of more company characteristics indicators, such as the abnormal turnover rate and the average turnover rate, etc., may give rise to the performance of different company characteristics indicators in the explanatory ability, and we can try to carry out a more detailed grouping inquiry. Third, the time dimension of future stock returns in this paper always stays at one month in the future, i.e., the short-term forecasting ability, and we can try to extend the future return performance to two months in the future, three months in the future, or even one year in the future, to explore the long-term forecasting ability of left-tailed risk.

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